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Factors Influencing Classroom Exposures to Fine Particles, Black Carbon, and Nitrogen Dioxide in Inner-City Schools and Their Implications for Indoor Air Quality

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Background: School classrooms, where students spend the majority of their time during the day, are the second most important indoor microenvironment for children.

Objective: We investigated factors influencing classroom exposures to fine particulate matter ($PM_{2.5}$), black carbon (BC), and nitrogen dioxide (NO_2) in urban schools in the northeast United States.

Methods: Over the period of 10 y (2008–2013; 2015–2019) measurements were conducted in 309 classrooms of 74 inner-city schools during fall, winter, and spring of the academic period. The data were analyzed using adaptive mixed-effects least absolute shrinkage and selection operator (LASSO) regression models. The LASSO variables included meteorological-, school-, and classroom-based covariates.

Results: LASSO identified 10, 10, and 11 significant factors ($p < 0.05$) that were associated with indoor $PM_{2.5}$, BC, and NO_2 exposures, respectively. The overall variability explained by these models was $R^2 = 0.679$, 0.687, and 0.621 for $PM_{2.5}$, BC, and NO_2, respectively. Of the model's explained variability, outdoor air pollution was the most important predictor, accounting for 53.9%, 63.4%, and 34.1% of the indoor $PM_{2.5}$, BC, and NO_2 concentrations. School-based predictors included furnace servicing, presence of a basement, annual income, building type, building year of construction, number of classrooms, number of students, and type of ventilation that, in combination, explained 18.6%, 26.1%, and 34.2% of $PM_{2.5}$, BC, and NO_2 levels, whereas classroom-based predictors included classroom floor level, classroom proximity to cafeteria, number of windows, frequency of cleaning, and windows facing the bus area and jointly explained 24.0%, 4.2%, and 29.3% of $PM_{2.5}$, BC, and NO_2 concentrations, respectively.

Discussion: The adaptive LASSO technique identified significant regional-, school-, and classroom-based factors influencing classroom air pollutant levels and provided robust estimates that could potentially inform targeted interventions aiming at improving children's health and well-being during their early years of development. https://doi.org/10.1289/EHP10007

Introduction

According to the World Health Organization (WHO), >90% of the world's children <15 years of age are exposed to ambient fine particulate matter [PM with an aerodynamic diameter of ≤2.5 μm ($PM_{2.5}$)] levels above WHO air quality guidelines (WHO 2018). Exposure to air pollution is a function of the amount of time and the frequency in each microenvironment, the concentration of the air pollutants in that specific microenvironment, and the activity-based uptake (inhalation dose) of each individual (Cepeda et al. 2017). School-age children are highly vulnerable to adverse health effects from exposure to air pollution because they are very active and breathe in more air (per body weight) than adults and because their respiratory and many other systems are still developing (Rückerl et al. 2011; Hoek et al. 2013). Exposure to particles with an aerodynamic diameter of ≤10 μm (PM_{10}) and 2.5 μm ($PM_{2.5}$) is associated with long-term deficits in lung function development (Gauderman et al. 2004), whereas exposure to nitrogen dioxide (NO_2) is associated with increases in airway inflammation, asthma exacerbations, and airflow obstruction (Takenoue et al. 2012; Orellano et al. 2017; Gaffin et al. 2018). Even at ambient pollutant levels below WHO guidelines, higher ambient air pollution exposures in children have been linked to increased asthma (Rice et al. 2018) and reduced lung function (Rice et al. 2016), whereas improvements in long-term childhood ambient pollution exposures have been associated with improvements in respiratory health (Urman et al. 2020; Garcia et al. 2021).

$PM_{2.5}$ has various sources, both anthropogenic and natural, whereas black carbon (BC) is part of $PM_{2.5}$ and is mainly formed by incomplete combustion of fossil fuels, wood, and other fuels (WHO 2021). NO_2 is a gaseous pollutant and forms when fossil fuels such as coal, oil, gas, or diesel are burned at high temperatures. Indoors, $PM_{2.5}$, BC, and NO_2 vary by location, time, and type of sources, having both common and unique sources. Primary schools are the second most important indoor microenvironment (other than the home) for children who typically spend >6 h/d in the school environment and may be exposed to elevated concentrations of $PM_{2.5}$, BC, and NO_2 (Carrion-Matta et al. 2019). Daily NO_2 levels measured inside schools around the globe may vary by a factor of 23, ranging from 6 to 68.5 $\mu g/m^3$ (Branco et al. 2015; Salonen et al. 2019), whereas $PM_{2.5}$ concentrations may fluctuate between 2.3 and 129 $\mu g/m^3$ (Carrion-Matta et al. 2019), indicating situations where U.S. Environmental Protection Agency and WHO

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ambient air quality guidelines are exceeded. Moreover, even indoor air pollution levels below these levels may affect child health. (Gaffin et al. 2018) found that mean weekly indoor school NO_2 levels >8 ppb were associated with airflow obstruction in asthmatic children from urban schools in a northeastern U.S. city. Therefore, it is critical to understand the sources and factors contributing to these substantial variations. Important potential sources of indoor $PM_{2.5}$, BC, and NO_2 include outdoor air pollution, smoking, gas stoves, heating, cleaning, dampness, mildew, moisture from water damage, pest infestation, and proximity to major roadways and industrial activities (Butz et al. 2011; Hansel et al. 2008; Matsui et al. 2007; Vette et al. 2013; Carrion-Matta et al. 2019). Factors related to the school environment that play an important role in exposure include temperature, relative humidity, and ventilation (Stabile et al. 2019; Reche et al. 2014; Weichenthal et al. 2008), building age and type (Che et al. 2021), occupancy level (Branco et al. 2019), and floor covering (Fromme et al. 2007). Given the limited number of samples and parameters examined, the contributions of sources, environmental factors and building characteristics that affect school- and classroom-based exposures have not been comprehensively addressed in the literature. Cooper et al. (2020) in their recent review and meta-analysis report that previous studies showed "lack of robust statistical analyses and inconsistent application of methodological approaches which led to considerable variation in results and weak evidence of significant and consistent associations between seasonal, meteorological, activity-based, site-based and ventilation rate variables with indoor $PM_{2.5}$ concentrations inside schools."

Aiming at closing some of these gaps and also identifying key controllable exposure aspects for managing schoolchildren's exposure to air pollutants, in the present study, we report indoor concentrations of $PM_{2.5}$, BC, and NO_2 from the School Inner City Asthma Study (SICAS) I and II and assess outdoor and indoor factors influencing classroom levels. We used an adaptive least absolute shrinkage and selection operator (LASSO) mixed-effects regression approach to identify key environmental-, school-, and classroom-related factors affecting children's exposure, and we quantified the joint and individual contributions of these factors to provide implications for school indoor air quality.

Methods

Study Design

The SICAS1 and SICAS2 investigated the association of school- and classroom-based environmental exposures on students with asthma in a northeastern U.S. city. SICAS1 study spanned 6 y (2008–2013) and included classroom exposure assessment twice per year (fall and winter or spring), whereas SICAS2 data spanned 5 y (2015–2019) and included baseline exposures during fall (October–November). SICAS1 was a 5-y prospective study evaluating the effects of school classrooms air quality on asthma morbidity for children with asthma attending urban public schools in low-income communities, whereas SICAS2 study was a factorial, randomized, placebo-controlled clinical trial conducted at 41 urban elementary schools designed to assess the efficacy of classroom air filtration in improving asthma control in children with active asthma. The rationale of SICAS1 and SICAS2 is described in detail elsewhere (Phipatanakul et al. 2011, 2017). Briefly, the enrolled subject's school classroom was assessed twice per year (fall and spring) for allergen, mold, and endotoxin levels. Indoor levels of $PM_{2.5}$, BC, and NO_2 were measured in a subset of these subjects' classrooms. At the beginning of the school year, research assistants also completed a school evaluation checklist, including ascertainment of the presence and use of gas stoves or electric kitchen stoves. Per confidentiality agreements, the locations of the schools may not be disclosed. Written parental informed consent and student assent were obtained in English or Spanish. The study protocol was approved by the Boston Children's Hospital institutional review board and by the principals at the participating schools. Information about the school, classroom characteristics, and the number of occupants were collected via a combination of questionnaires, inspection, and interviews with the staff. Survey data were ascertained in person or by telephone by staff, and the response numbers (per year) depended upon the number of students enrolled from each school. Students who fulfilled the inclusion criteria were eligible for the trial, randomization of their classrooms and schools, and measurement of indoor air pollution exposures. Inspections in the schools and classrooms were conducted by SICAS staff before each measurement campaign (twice for SICAS1 and once for SICAS2). Occupancy periods varied between different studied classrooms, varying not only due to the children being in preschool or high school but also on each school organization. Starting and ending times varied between 0715–0930 and 1400–1610 hours, respectively, which are typical timetables for education in the United States.

Instrumentation and Data Collection

Weeklong indoor $PM_{2.5}$, BC, and NO_2 measurements were conducted in inner-city school classrooms during weekdays, incorporating both occupied and nonoccupied periods. $PM_{2.5}$ samples were collected using a personal exposure monitor (PEM) in school classrooms in one or two seasons during the academic school years between 2008 and 2013 for SICAS1 and during one season, fall or winter, for SICAS2 between 2015 and 2019. PEM includes an inertial impactor designed specifically for personal or indoor sampling (Demokritou et al. 2001). Personal $PM_{2.5}$ samples were collected on Teflon filters at a flow rate of $1.8\ L/min$ for SICAS1. For SICAS2, a cascade impactor (Demokritou et al. 2002) with a collection rate of $5L/min$ was used. A total of 518 indoor $PM_{2.5}$ samples were collected during the study period corresponding to 309 classrooms of 74 schools. $PM_{2.5}$ mass were measured gravimetrically where, Teflon filters, including blanks, were weighed pre- and postmeasurement with an electronic microbalance (MT-5 Mettler Toledo) and conditioned for a 48-h period in a controlled temperature ($22 \pm 1.5°C$) and relative humidity ($40 \pm 5\%$) room. Following the postmeasurement weighing, the indoor filters were also measured for BC concentrations using a Smokestain Reflectometer (Model EEL M43D, Diffusion Systems Ltd.). Indoor NO_2 was collected in passive Ogawa samplers (weekday periods), and the levels were quantified by ion chromatography. Concurrent daily outdoor $PM_{2.5}$, BC, and NO_2 concentrations were also measured at a central monitoring supersite. $PM_{2.5}$ samples were collected using a Harvard Impactor (Koutrakis et al. 1993), BC concentrations were measured using a single ($\lambda = 880$ nm) channel aethalometer (model AE-16, Magee Scientific), and NO_2 was measured with chemiluminescent analyzers. Indoor and outdoor samples were compared by matching the weekly indoor samples to the corresponding outdoor samples. The supersite was located within 12 km of the schools (range: 1,065–11,592 m), with a median distance between the central supersite and schools of 4,974 m. Although the central site was part of the urban agglomeration, it was located 20 m above ground level and was considered a suitable urban background station for the area (Gaffin et al. 2017).

Statistical Analysis

To identify predictive variables for classroom exposures to $PM_{2.5}$, BC, and NO_2, we applied a mixed-effects model with the LASSO variable selection process (Tibshirani 1996; Zou 2006), a technique often used for drug identification in cancer treatments

(Geeleher et al. 2014). In the models, we controlled for continuous variables of outdoor $PM_{2.5}$, BC, and NO_2, temperature (T), wind speed (ws), seasonality [$\mathrm{cosd} = \cos(2 \times \pi \times d/365)$] and floor level of classroom (four levels; Table 1) because these variables have been reported as important indoor exposure predictors (Habre et al. 2014; Gaffin et al. 2017; Huang et al. 2018). These covariates were included in the models and their fixed effects were estimated with no penalization.

Identifying important predictors from a large list of variables is challenging because methods such as stepwise regression ignore stochastic errors in the stages of variable selection and can result in false confidence intervals (Fan and Li 2001; Harrell 2001). The adaptive LASSO method can overcome these limitations because it applies a tuning parameter to penalize variables from the full list of variables in the model. Here, the adaptive LASSO was applied to select important determinants that may be associated with exposure to $PM_{2.5}$, BC, and NO_2 in inner-city schools. The LASSO is a regression shrinkage and variable selection approach that applies a penalty to the absolute size of the regression coefficients based on the value of a tuning parameter being less than a given value (Tibshirani 1996). The adaptive LASSO is a later version of the LASSO, which uses weights for penalizing different coefficients (Fan and Li 2001; Zou 2006). Because schools had repeated measurements, and to account for the spatiotemporal variations between each school and the central supersite, we fit linear mixed-effects models with random school-specific slopes and intercepts to capture the correlation among different measurements within the same school, as follows:

$$Y_{ij} = X_{ij}\alpha + Z_{ij}\beta + \mu_{ij} + u_{ij} + \varepsilon_{ij},$$

where Y_{ij} is the log of indoor exposure of $PM_{2.5}$, BC, and NO_2 in classroom i and school j; $X_i = (X_{i1}, X_{i2}, X_{iP})^T$ is a vector of outdoor $PM_{2.5}$, BC, and NO_2 levels and other covariates; $Z_i = (Z_{i1}, Z_{i2}, Z_{iP})^T$ is a vector of school and classroom characteristics; μ_i is the random intercept; u_i is the random slope; and ε_i is the error. Hence, α indicates the fixed effects of outdoor $PM_{2.5}$, BC, NO_2, and other covariates X_i; and β is the penalized effects of school/classroom characteristics Z_i that are given by the adaptive LASSO.

To obtain nonzero coefficients (β_{lme}) for each variable in LASSO, we applied an ordinary linear mixed-effects (OLME) model and computed the adaptive weight (w) as its inverse ($w = 1/\beta_{lme}$). This approach gives less weight in the penalty to variables whose coefficients are large because they have increased likelihood of being predictors (Dai et al. 2016). In the adaptive LASSO, a nonnegative penalty parameter, λ, determines how strongly the regression coefficients are being constrained. A small λ value means that there is no shrinkage, and the regression coefficients are weakly penalized and reflect those in a regular linear mixed-effects regression model. A large λ value means that there is maximum shrinkage, resulting in a model that includes fixed covariates only. A λ with in-between values means that the model is a penalized model and that some coefficients are 0, whereas the remaining nonzero coefficients are selected by the adaptive LASSO. In this way, the method chooses variables from school characteristics that may be associated with indoor exposure. Cross-validation (CV) was used to identify the tuning parameter λ and in turn identify statistically predictive variables for indoor exposure related to $PM_{2.5}$, BC, and NO_2. Last, we used the mixed-effects model with fixed covariates and LASSO-selected variables only to obtain the estimated indoor exposure relationships.

The collinearity among predictors in the multiple linear regression models was examined using variance inflation factors (VIFs), which measure how much the variance of an estimated regression coefficient is increased due to collinearity. Predictors with VIF values >10, are signs of multicollinearity (O'brien 2007). A conditional R^2 was applied to investigate the proportion of total variance explained through both fixed and random effects (Nakagawa and Schielzeth 2013), whereas a partial R^2 was used to provide insight into the proportion of variation that can be explained by the explanatory variables. In the models, the continuous variables we included were temperature, wind speed, seasonality, indoor and outdoor pollutant concentrations, whereas all the other variables were categorical. Table 1 summarizes the variables in the models. In the models, "attached schools" were defined as those that had

Table 1. Inner-city school ($n = 74$)- and classroom ($n = 309$)-based characteristics [n (%)].

Characteristics	Categories	Schools	Classrooms
Building type	Attached	13 (17.6)	—
	Detached	61 (82.4)	—
Built year	Prior to 1950	48 (65)	—
	After 1950	26 (35)	—
Ventilation	Natural	38 (51.4)	100 (47.8)
	Mixed	18 (24.3)	26 (12.4)
	Mechanical	12 (16.2)	35 (16.7)
Annual income	>\$45,000	35 (47.3)	—
	≤\$45,000	39 (52.7)	—
Classroom regular cleaning	Yes	—	62 (20.0)
Classroom floor level	Ground level	—	15 (4.8)
	1st	—	99 (32.0)
	2nd	—	145 (46.9)
	3rd	—	50 (16.18)
Number of classrooms	>30	32 (43.2)	—
	≤30	42 (56.8)	—
Basement	Yes	48 (64.9)	—
	No	25 (33.7)	—
Classroom AC	Yes	—	70 (22.6)
	No	—	239 (77.3)
Classroom near cafeteria	Yes	—	58 (18.8)
	No	—	251 (81.2)
Signs of mildew	Ceiling	—	28 (9)
	Walls	—	8 (2.5)
	Windows	—	12 (3.8)
Moisture leaks	Yes	—	61 (19.7)
	No	—	248 (80.3)
Floor material	Carpet	—	97 (31.4)
	Rug	—	182 (58.9)
	>1	—	71 (35.5)
	Tile	—	161 (52.1)
	Wood	—	121 (39.2)
Floor rating	Poor	—	100 (32.4)
	Fair	—	68 (22.0)
	Intact	—	132 (42.7)
Windows' rating	Poor	—	96 (31.1)
	Fair	—	76 (36.4)
	Intact	—	133 (63.6)
Walls' rating	Poor	—	95 (30.7)
	Fair	—	109 (35.2)
	Intact	—	112 (36.2)
Walls' paint	Poor	—	90 (29.1)
	Fair	—	130 (42.1)
	Intact	—	96 (31.1)
Windows' paint	Poor	—	99 (32.0)
	Fair	—	60 (19.4)
	Intact	—	131 (42.4)
Musty	Yes	—	25 (8)
	No	—	283 (91.5)
Windows (n)	≥5	—	179 (57.9)
	<5	—	130 (42.1)
Windows location	Bus area	—	98 (31.7)
Furnace age	≤20 y	13 (17.6)	—
	>20 y	32 (43.2)	—
Furnace last serviced	≤1 y	41 (55.4)	—
	>1 y	20 (27)	—
Use of gas stoves for cooking	Yes	8 (10.8)	—
	No	66 (89.2)	—

Note: —, not applicable; AC, air conditioning.

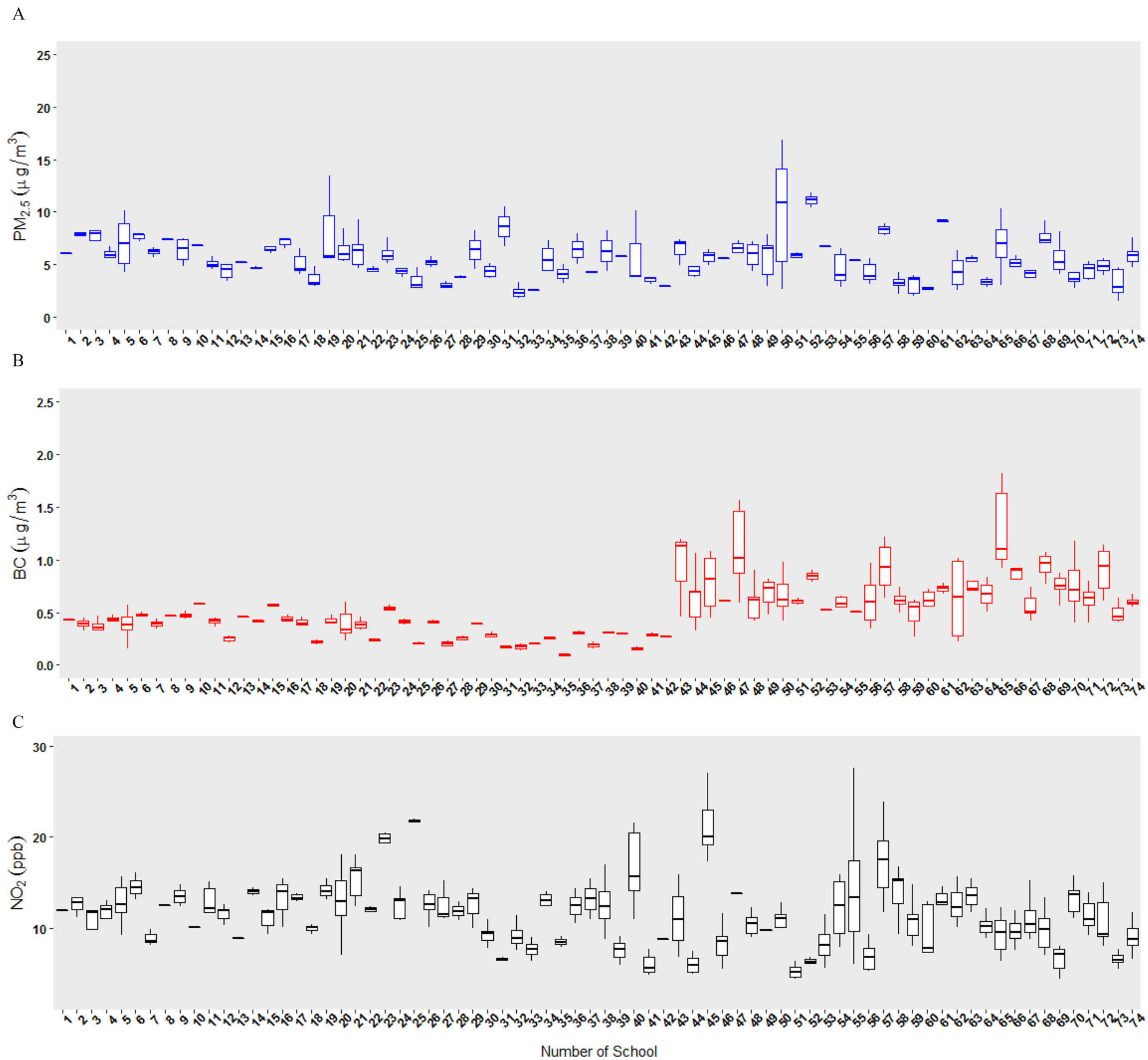

Figure 1. Distribution of (A) $PM_{2.5}$, (B) BC, and (C) NO_2 concentrations by school ($n = 74$). The numbers on the x-axis represent each school. Box and whiskers plots represent the distribution of $PM_{2.5}$, BC, and NO_2 across multiple classrooms within each school. Box parameters are the interquartile range (IQR), the hash mark is the median, and whiskers extend to 1.5 times the IQR above the 75th and below the 25th percentiles. For full descriptive statistics for each school, see Table S1. Note: BC, black carbon; NO_2, nitrogen dioxide; $PM_{2.5}$, PM with an aerodynamic diameter of ≤ 2.5 μm (fine particulate matter).

one or more buildings touching or that were part of a group of buildings, and "detached schools" were defined as those that had buildings that were not touching any other buildings. Annual income was calculated for schools; if most of the school population had a household income >\$45,000, it was defined as "low middle-class income" (Kochhar 2018).

To determine the indoor $PM_{2.5}$ of outdoor origin, we used the sulfur ratio approach (Sarnat et al. 2002). This assumes that when there are no indoor sources of sulfur, the indoor penetration of $PM_{2.5}$ emitted from outdoor sources can be approximated by the indoor to outdoor ($sulfur_{indoor}/sulfur_{outdoor}$) ratio (Long and Sarnat 2004). This is based on the assumption that sulfur origin is from long-range transport, hence the measurements from the outdoor central supersite can be representative of the whole region (Huang et al. 2018; Matthaios et al. 2021). The sulfur ratio was calculated for each school classroom and classroom sampling period, and it was then multiplied by the outdoor concentration to approximate the infiltration fraction and the fraction of indoor $PM_{2.5}$ that come from outdoor sources (Habre et al. 2014). To reflect this process in our modeling approach, we included random slopes and intercepts, taking into account the spatiotemporal variation between the central supersite and each school.

Results

School Characteristics

Characteristics of the studied microenvironments are listed in Table 1. Briefly, the schools varied widely in age (built between 1899 and 2002, with many built before the 1950s) and in the

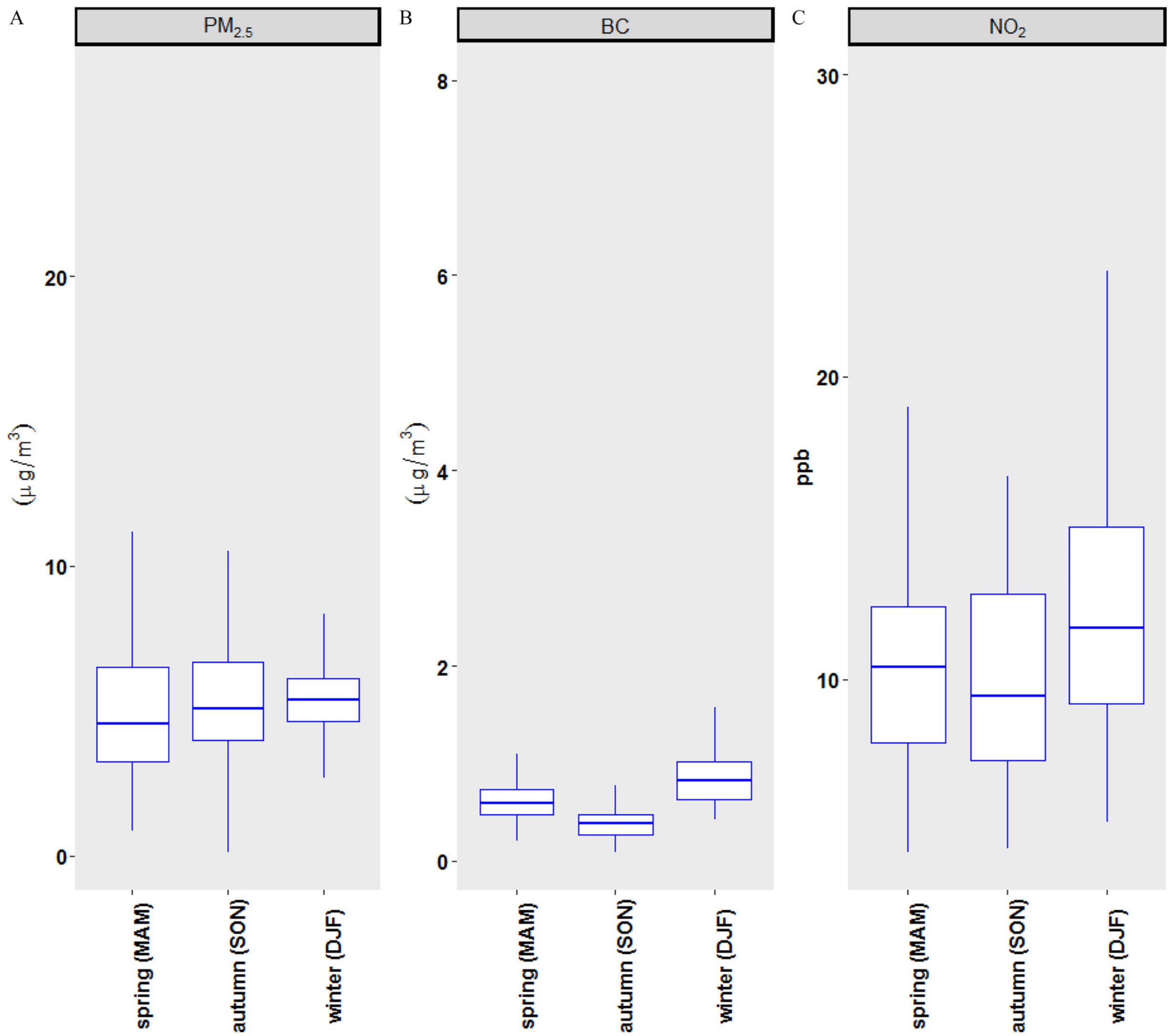

Figure 2. Within-school ($n = 74$) concentrations of (A) $PM_{2.5}$, (B) BC, and (C) NO_2, during spring (MAM: March, April, May), fall (SON: September, October, November) and winter (DJF: December, January, February). Box parameters are the interquartile range (IQR), the hash mark is the median, and whiskers extend to 1.5 times the IQR above the 75th and below the 25th percentiles. For full descriptive statistics, see Table S2. Note: BC, black carbon; NO_2, nitrogen dioxide; $PM_{2.5}$, PM with an aerodynamic diameter of ≤ 2.5 µm (fine particulate matter).

type of ventilation (natural, mechanical, and mixed). The mean occupant density in classrooms was $8\ \text{children}/100\ m^2$ (range: 4–20 $\text{children}/100\ m^2$), which is in compliance with the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) guidelines for school facilities (i.e., 25 $\text{occupants}/100\ m^2$) (ASHRAE 2007).

Classroom levels of $PM_{2.5}$, BC, and NO_2

The mean $\pm$ standard deviation (SD) levels of $PM_{2.5}$, BC, and NO_2 were $5.7 \pm 1.4\ \mu g/m^3$, $0.6 \pm 0.16\ \mu g/m^3$ and 11.5 ± 1.8 ppb, with the respective ranges of 0.13–27 $\mu g/m^3$, 0.09–0.99 $\mu g/m^3$, and 2.3–29.7 ppb. The median concentration levels were $5.4\ \mu g/m^3$ ($PM_{2.5}$), $0.56\ \mu g/m^3$ (BC), and 10.9 ppb (NO_2). Figure 1 shows the school-based exposure variability of $PM_{2.5}$, BC, and NO_2 across the 74 schools during 2008–2013 and 2015–2019, and the full descriptive statistics are listed in Table S1. $PM_{2.5}$, BC, and NO_2 exposures during winter period were significantly ($p < 0.05$) greater from those measured during fall and spring. Figure 2 shows the seasonal variation of indoor $PM_{2.5}$, BC, and NO_2 during the 10-y measurement period (see Table S2 for descriptive statistics). In general, levels of $PM_{2.5}$ and NO_2 were low; however, we observed 20 classrooms in 10 schools with $PM_{2.5} > 12\ \mu g/m^3$, all associated with classrooms that had more than six windows facing toward the bus drop-off and pick-up area.

Factors Affecting Indoor Exposure

Table 2 shows the results of the adaptive LASSO mixed-effects model. Using cross-validation we selected the lambda for $PM_{2.5}$, BC, and NO_2 models. For $PM_{2.5}$, BC, and NO_2, the minimum mean square error in cross-validation comes when $\log(\lambda) = -4$, -2.2, and 5, whereas 1 standard error (SE) has a $\log(\lambda) = 2.1$, 3.6, and 8.8, respectively. Generally, the purpose of regularization is to balance accuracy and simplicity, meaning a model with the smallest number of predictors that also gives a good accuracy. To this end, we selected the value of lambda that gave the simplest model while also lying within 1 SE. Figures S1–S3 show that the model predicts well each pollutant when $\log(\lambda) = 2.1$, 3.6, and 8.8 and that the model within 1 SE at 6, 6, and 7 variables of the total 67 was also a good choice for each pollutant respectively. From the LASSO predictors listed in Table 2, it is evident that indoor exposure to all three examined pollutants was

Table 2. Determinants of classroom $PM_{2.5}$, BC, and NO_2 levels in schools ($n = 74$) and classrooms ($n = 309$), as reported by the adaptive LASSO mixed-effects model.

	$PM_{2.5}$ model ($N = 388$)				BC model ($N = 396$)				NO_2 model ($N = 362$)			
Influencing factor	Coef $\pm$ SE	p-Value	VIF	RI	Coef $\pm$ SE	p-Value	VIF	RI	Coef $\pm$ SE	p-Value	VIF	RI
Outdoor origin factors												
Outdoor concentration	0.39 ± 0.031	<0.01	1.74	53.9	0.54 ± 0.025	<0.01	1.25	63.4	0.36 ± 0.042	<0.01	1.44	34.1
Ambient temperature	0.02 ± 0.042	0.054	1.48	1.3	-0.04 ± 0.042	0.058	1.83	3.1	-0.02 ± 0.042	0.09	1.48	1.0
Seasonality	—	—	—	—	-0.05 ± 0.018	<0.01	1.27	1.7	—	—	—	—
Wind speed	-0.03 ± 0.014	0.018	1.65	2.2	-0.07 ± 0.017	<0.01	1.22	4.1	-0.03 ± 0.015	0.062	1.40	1.5
School origin factors												
Furnace last serviced	—	—	—	—	0.05 ± 0.006	<0.01	1.10	19.0	—	—	—	—
Presence of a basement	—	—	—	—	0.08 ± 0.022	<0.01	1.08	3.6	—	—	—	—
Annual income (>45k)	-0.06 ± 0.024	<0.01	1.15	2.8	—	—	—	—	-0.11 ± 0.029	<0.01	1.20	8.1
Building type	—	—	—	—	0.07 ± 0.041	0.069	1.16	0.7	-0.08 ± 0.035	0.021	1.63	2.5
Year of construction	-0.07 ± 0.012	<0.01	1.15	12.4	—	—	—	—	—	—	—	—
Classrooms (n)	—	—	—	—	—	—	—	—	0.05 ± 0.014	<0.01	1.67	8.1
Students (n)	—	—	—	—	—	—	—	—	0.06 ± 0.021	<0.01	1.46	5.3
Type of ventilation	0.01 ± 0.003	<0.01	1.13	3.4	—	—	—	—	0.02 ± 0.004	<0.01	1.46	10.2
Classroom origin factors												
Floor level	-0.06 ± 0.014	<0.01	1.25	7.9	—	—	—	—	-0.03 ± 0.015	0.023	1.13	3.1
Proximity to cafeteria	0.10 ± 0.035	<0.01	1.20	3.4	—	—	—	—	—	—	—	—
Windows (n)	0.01 ± 0.004	<0.01	1.26	5.9	—	—	—	—	0.02 ± 0.003	<0.01	1.30	14.9
Cleaning frequency	—	—	—	—	0.13 ± 0.038	<0.01	1.12	2.8	—	—	—	—
Windows facing bus area	0.09 ± 0.024	<0.01	1.16	6.8	0.08 ± 0.036	0.027	1.14	1.4	0.15 ± 0.028	<0.01	1.19	11.3

Note: —, not applicable; BC, black carbon; coef, coefficient of predictor; LASSO, least absolute shrinkage and selection operator (regression model); NO_2, nitrogen dioxide; $PM_{2.5}$, PM with an aerodynamic diameter of ≤ 2.5 μm (fine particulate matter); RI, relative importance of predictors; SE, standard error of the coefficient; VIF, variance inflation factor (values close to 10 indicate collinearity).

found to be associated with different characteristics related to school, classroom, and outdoor conditions.

Overall, the $PM_{2.5}$ LASSO mixed-effects model explained 67.9% of classroom $PM_{2.5}$ variability, suggesting that the selected parameters reflected the key processes affecting indoor PM concentrations. Classroom $PM_{2.5}$ exposures were significantly ($p < 0.05$) positively associated with outdoor $PM_{2.5}$ levels and ambient temperature ($p < 0.1$) and significantly inversely associated with wind speed. From the final $PM_{2.5}$ LASSO mixed-effects model, the outdoor $PM_{2.5}$ concentration was by far the largest and most important predictor and explained 53.9% of the variability, whereas the ambient meteorological parameters explained an additional 3.5%. Furthermore, indoor $PM_{2.5}$ concentrations were significantly ($p < 0.05$) positively associated with schools that had natural ventilation, whereas school year of construction and annual income of >$45,000 were negatively associated with indoor $PM_{2.5}$ levels. These school building, envelope-related, and disparity characteristics together explained 15.2% of the $PM_{2.5}$ variance. Classrooms with more windows and those close to the school's cafeteria were significantly ($p < 0.05$) positively associated with indoor $PM_{2.5}$ exposure and combined accounted for 9.3% of $PM_{2.5}$ variability. Classrooms with windows facing the bus area were significantly positively associated with indoor $PM_{2.5}$ concentrations and explained 6.8% of the $PM_{2.5}$ indoor exposures, whereas classrooms located at greater levels were significantly negatively associated with indoor $PM_{2.5}$ exposures. In the $PM_{2.5}$ model, environmental factors were the most important predictors, explaining 57.4% of the classroom $PM_{2.5}$ exposures. School-originated predictors explained 18.6%, whereas classroom-based factors accounted for 24.0% of the $PM_{2.5}$ variance.

The LASSO mixed-effects model for BC exposure explained 68.7% of BC variability, indicating that it captured the key factors and sources affecting classroom BC levels. Indoor BC levels were significantly ($p < 0.05$) positively associated with outdoor BC concentrations and negatively associated with ambient temperature ($p < 0.1$), seasonality, and wind speed. Outdoor BC explained 63.4% of the BC LASSO mixed-effects model variation, whereas ambient temperature, seasonality, and wind speed combined accounted for 8.9%. Regarding school characteristics, BC was significantly positively associated with attached buildings ($p < 0.1$), the presence of a basement and time since furnace servicing ($p < 0.05$). Furnace servicing presented a considerable indoor predictor, accounting for 19.0%, whereas the remaining school-related factors explained 4.3% of indoor BC levels. Classroom floor level, despite being added into the model without penalization, did not associate with indoor BC levels. Classrooms that were not cleaned regularly and those with windows facing the bus drop-off and pick-up area, together accounting for $\sim 4\%$ of the BC variability, were significantly positively associated ($p < 0.05$) with BC levels. In the LASSO mixed-effects model, outdoor factors were the most important ones and combined explained 72.3% of indoor BC exposures, whereas school- and classroom-based related factors explained the remaining 26.1% and 4.2% of indoor BC levels, respectively.

The LASSO mixed-effects model for NO_2 explained 62.1% of classroom exposure variability and had both unique and similar predictors to $PM_{2.5}$ and BC LASSO mixed models. Outdoor concentration, which was a significant and common predictor in all the models, was positively associated with indoor NO_2 and explained 34.1% of the model's variability, whereas ambient temperature and wind speed (also predictors for $PM_{2.5}$ and BC) were negatively associated ($p < 0.1$), with indoor NO_2, accounting for another 1.0% and 1.5%, respectively. School factors, such as a greater number of classrooms and a greater number of students, were unique for the NO_2 model and were significantly positively associated with NO_2 concentrations. Income >45K, as in the $PM_{2.5}$ model, was significantly negatively associated with NO_2 levels, whereas attached buildings (contrary to the BC model) were negatively associated with NO_2 exposure. School-related characteristics combined accounted for 34.2% of the NO_2 variability. Classrooms with more windows or windows facing the bus area were positively associated with NO_2 exposures, whereas classrooms located at higher levels, were negatively associated with indoor NO_2 exposures. Number of classroom windows and location window, which was an important and common predictor for all models, combined accounted of 26.2% of the variability, whereas classrooms located at greater levels accounted for 3.1% of indoor exposure variation, respectively. Within-school NO_2 exposure was influenced almost equally by environmental-, school- and classroom-based factors,

Table 3. Indoor $PM_{2.5}$, BC, and NO_2 concentrations and possible influencing factors from various schools across the world.

Study	Location	Schools (area)	Concentrations ($\mu g/m^3$) $PM_{2.5}$	BC	NO_2	Ventilation system	Influencing factors
This study	Northeastern USA	74 (urban)	5.7	0.6	11.5	Mixed	Infiltration, ventilation, seasonality, number/location of windows, cleaning frequency, age of building, number of students, proximity to cafeteria, furnace condition
Majd et al. 2019	Baltimore, Maryland, USA	16 (urban)	7.2	—	28.7	Mainly mechanical	Infiltration, seasonality, proximity to road, classroom level
Hochstetler et al. 2011	Ohio, USA	4 (urban)	15.6	0.26	—	Natural	Cafeteria, gym, indoor dust resuspension, open windows and doors
Zhang and Zhu, 2012	Texas, USA	1 (urban)	4.3	—	—	—	Heaters, food-related activities, cleaning, painting, ventilation
Bozlaker et al. 2017	Texas, USA	1 (urban)	3.2	—	—	Mechanical	Infiltration, ventilation
Raysoni et al. 2013	Texas, USA	3 (urban)	10.6	0.28	7.9	Mechanical	Infiltration, air exchange rate, building tightness, indoor dust resuspension
Polidori et al. 2013	Los Angeles, California, USA	3 (urban)	6.6	3.05	—	Mechanical	Indoor HEPA filters effectiveness
Rivas et al. 2014	Barcelona, Spain	39 (urban)	37	1.3	30	Natural	Infiltration, sand-filled playgrounds, cooking, chalk, proximity to road
Branco et al. 2019	Portugal	8	37.6	—	47.4	Natural	Seasonality, private/public, flooring material, indoor background dust
Stranger et al. 2008	Antwerp, Belgium	11 (urban)	59	0.4	73	Natural	$PM_{2.5}$: indoor dust resuspension, carpets, BC, and NO_2: seasonality, air exchange, deposition velocity
Rosbach et al. 2016	Northeastern Netherlands	17 (urban)	17.4	—	19	—	Ventilation
Buonanno et al. 2013	Cassino, Italy	3 (urban)	—	13.9	—	Natural	Local traffic
Wichmann et al. 2010	Stockholm, Sweden	6 (urban/suburban)	8.1	0.7	17.3	Mechanical	$PM_{2.5}$: indoor sources BC and NO_2: infiltration factors ventilation type and air exchange rate
Chatzidiakou et al. 2015a, 2015b	London, UK	3 (urban)	36	—	25	Natural	Heating, infiltration, proximity to road
Fromme et al. 2007; 2008	Munich, Germany	64	30.5	2.6	—	Natural	Indoor temperature and RH, classroom size, classroom level, occupancy
Diapouli et al. 2008	Athens, Greece	7 (urban)	82	—	—	—	Infiltration, carpet floor, room size
Broekstra et al. 2019	Berlin, Germany	10	7.5	—	10.6	—	Infiltration, traffic
	London, UK	6	2.2	—	17.8	—	Infiltration, ventilation
	Madrid, Spain	12	3.4	—	27.3	—	Infiltration, traffic
	Paris, France	6	6.3	—	21.3	—	Infiltration, road proximity
	Sofia, Bulgaria	8	23.2	—	16.4	—	Outdoor air pollution
Jovanović et al. 2014	Serbia	1	43.56	—	15	Natural	Ventilation, carpet floor, window condition
Paunescu et al. 2017	Paris, France	Urban	—	1.54	—	—	Infiltration, time of day, window opening
Che et al. 2021	Hong Kong, China	32 (urban)	23	—	47.8	Natural and mechanical	Infiltration, room type, occupancy, use of blackboard, flooring material
Zhou et al. 2020	Chengdu, China	Urban	—	3.6	—	—	Background levels, seasonality, meteorology
Jeong and Park, 2017	Seoul, Korea	Urban	—	1.93	—	—	Infiltration, proximity to local sources
Chithra and Nagendra (2012)	Chennai, India	1 (urban)	46.5	—	—	Natural	Infiltration, outdoor meteorology, traffic
Mohd Isa et al. 2020	Selangor, Malaysia	8 (urban)	24.6	—	32	—	Infiltration, ventilation
Portela et al. 2021	Canoas, Brazil	1 (urban)	—	3.1	—	—	Infiltration and local traffic
Al-Hemoud et al. 2017	Kuwait	7 (urban)	—	—	30.2	Mechanical	Seasonality, indoor burners

Note: —, not applicable; BC, black carbon; HEPA, high-efficiency particulate air (filter); NO_2, nitrogen dioxide; $PM_{2.5}$, PM with an aerodynamic diameter of ≤ 2.5 μm (fine particulate matter).

where environmental factors predicted just over one-third (36.6%) of the indoor NO_2 exposures and school- and classroom-originated predictors explained 34.2% and 29.3%, respectively.

Discussion

The present study investigated factors affecting children exposures to $PM_{2.5}$, BC, and NO_2 in inner-city schools in the northeast United States. Despite the fact that our results address only urban schools, exposure to $PM_{2.5}$, BC, and NO_2 were mostly low compared with other studies performed in other U.S. areas (Hochstetler et al. 2011; Zhang and Zhu, 2012; Raysoni et al. 2013; Polidori et al. 2013; Bozlaker et al. 2017; Majd et al. 2019), Europe (Fromme et al. 2007, 2008; Diapouli et al. 2008; Stranger et al. 2008; Wichmann et al. 2010; Buonanno et al. 2013; Rivas et al. 2014; Jovanović et al. 2014; Chatzidiakou et al. 2015a, 2015b; Rosbach et al. 2016; Paunescu et al. 2017; Broekstra et al. 2019; Branco et al. 2019), China (Che et al. 2021; Zhou et al. 2020), Korea (Jeong and Park, 2017), India (Chithra and Nagendra, 2012), Malaysia (Mohd Isa et al. 2020), Brazil (Portela et al. 2021), and Kuwait (Al-Hemoud et al. 2017). Table 3 lists similar studies across the world and refers to determinants influencing classroom exposures to these pollutants.

Our results showed that outdoor concentrations were an important factor with significant impacts on indoor exposure levels, which is in agreement with the majority of the studies in Table 3, where the most critical factor influencing classroom exposures was infiltration of outdoor air pollution. Seasonality and meteorological parameters (temperature and wind speed) were also important factors. Seasonality was shown to be associated with the indoor concentrations of all examined pollutants. Higher BC and NO_2 concentrations were observed in winter, which is consistent with the findings of the previous studies (Blondeau et al. 2005; Fromme et al. 2007; Goyal and Khare, 2009; Majd et al. 2019). Our results showed a positive association of temperature with indoor $PM_{2.5}$ concentrations presumably as a result of enhanced secondary aerosols, similar to previous studies (Braniš et al. 2005; Goyal and Khare, 2009; Majd et al. 2019), and inverse associations with BC and NO_2. The negative association between temperature and BC and NO_2 in urban environments during cold season likely relates to the efficacy of the vehicle after-treatment systems and the proportion of vehicles running under normal operating temperature vs. cold start conditions (Matthaios et al. 2019). Wind speed was also significantly inversely associated with all the pollutants. Low wind speeds translate to poor dispersion conditions in the atmosphere, which in turn leads to accumulation of pollution in the lower troposphere near the surface (Matthaios et al. 2017). This results into elevated outdoor levels and thus elevated indoor exposure.

The analysis also showed that school-related factors important to exposure included frequency of furnace servicing and building characteristics linked to the air tightness of the building envelope such as the presence of a basement, construction age, and whether the school was attached or detached from other buildings. Building envelope characteristics differently influence each pollutant. Year of construction was negatively associated with $PM_{2.5}$ exposures. Older buildings are "leaky," and they tend to have more cracks and openings, which favor the infiltration of outdoor particles (Breen et al. 2014). Similar results were found by (Che et al. 2021), where $PM_{2.5}$ concentrations in schools >40 years of age were, on average, $3.5\ \mu g/m^3$ greater than those built within 20 y. As demonstrated by our analysis, attached buildings were associated with greater BC levels, whereas detached buildings were associated with elevated NO_2 levels. Detached schools were mostly located near major roads and, therefore, were more impacted by traffic-related pollutants such as NO_2. The importance of heating that was an important factor for indoor BC levels was also reported in similar inner-city schools study in Baltimore (Majd et al. 2019) and Texas (Zhang and Zhu 2012), as well as in other studies in England (Chatzidiakou et al. 2015a, 2015b) and Portugal (Branco et al. 2019). Our results also showed significant associations of $PM_{2.5}$ and NO_2 with low annual income, which is in agreement with studies that highlighted the importance of socioeconomic disparities with air pollution exposure (Hajat et al. 2015). The association of NO_2 with a greater number of classrooms and a greater number of students is another indication of disparity given that in the U.S. bigger schools with more students tend to be located in poor neighborhoods that are more influenced by traffic-related pollutants (Kravitz-Wirtz et al. 2018).

Classroom-related factors important for exposure included classroom level floor, frequency of cleaning, number of windows, and window location (i.e., facing bus area). Higher classroom floor level was negatively associated with NO_2 and $PM_{2.5}$ concentrations. Classrooms located at lower floors are closer to nearby outdoor emission sources and may be influenced by buses during drop-off and pick-up times (Guo et al. 2010). Measurements of vertical profiles of $PM_{2.5}$ and NO_2 in city-center buildings showed that $PM_{2.5}$ had a decline of 11% with height, whereas traffic-related pollutants such as NO_2 showed a much stronger decline of 74% (Sajani et al. 2018). This supports our findings of significant negative associations between $PM_{2.5}$ and NO_2 and classroom floor. Furthermore, the observed positive association between exposures and the number of open windows in a classroom is related to the larger penetration of outdoor pollutants. We found that classrooms with windows facing the bus area influence indoor exposures of all pollutants. In agreement with our results, $PM_{2.5}$ in schools during drop-off hours were found to be two to three times greater (Kumar et al. 2020), whereas schools with a greater number of buses were also found to have greater $PM_{2.5}$ and BC concentrations indoors (Hochstetler et al. 2011). The school cafeteria was found to have a positive association with $PM_{2.5}$ classroom exposures that is in agreement with a study in Ohio that reported elevated $PM_{2.5}$ concentrations during the cafeteria opening hours (Hochstetler et al. 2011). Despite knowing that indoor cooking is an important source for $PM_{2.5}$, BC, and NO_2, in our study only 10.8% of the schools did active cooking in the premises and for the majority of the schools the food was cooked and delivered by catering services. Occupancy can impact PM levels in classrooms, especially the coarse fraction (Branco et al. 2019; Che et al. 2021), owing to the resuspension of particles (Fromme et al. 2007); however, in this study we could not assess occupancy directly given that the measurements were weeklong and included both occupancy and nonoccupancy periods.

Overall, LASSO mixed-effects regression models for $PM_{2.5}$, BC, and NO_2 revealed different influences from multiple factors that are related to both outdoor and indoor conditions. Indoor factors associated with exposures further varied with school and classroom characteristics, revealing the complexity of the problem and the additional research that is needed to determine the causality of these relationships. Our study also has a few limitations: The classroom exposures reported here might not be representative for long-term measurements of children's exposure inside schools given that they were not continuous over the 10-y period. Furthermore, the exposures might not be representative for other inner-city schools because each urban agglomeration has different sources and each school has different management policies, building characteristics, ventilation practices, and indoor activities that may not be found elsewhere. The integrated samples included both occupancy and nonoccupancy periods during the week; thus, the measured exposures may be lower than those experienced when the children are in school. Road proximity, which can often be a traffic-related exposure factor (Huang et al. 2018), was not included in the analysis. Despite including building age in our analysis, which has an effect of air tightness of the building, we did not account for any building improvements in the schools, which have been shown to improve the overall indoor air quality (Majd et al. 2019).

Implications

This work examined predictors of classroom exposures to air pollutants in inner-city schools using an adaptive LASSO mixed-effects regression method. The results obtained were based on an extensive set of field measurements performed for indoor and outdoor concentrations of particle and gaseous air pollutants in 309 classrooms at 74 schools and information collected via a combination of questionnaires, inspection, and interviews with the staff. Such measurements provide a basis for the comprehensive quantification of exposure impacts from multiple factors and add to the robustness of the estimates. The relatively low $PM_{2.5}$, BC, and NO_2 concentrations measured inside schools may represent a partial ongoing success story for environmental equity for these urban schools that have had to deal with the many structural indoor and outdoor challenges of old school buildings located in poor neighborhoods, where they are often surrounded by city traffic and multiple other potentially adverse environmental exposures. A policy of delivering meals from a central source may have also decreased indoor kitchen-related exposures, whereas state- and city-wide campaigns to reduce bus and private cars idling around schools and programs to retrofit school buses may have also contributed to that direction. Despite the low indoor $PM_{2.5}$ levels, past studies of children as well as adults have reported adverse health effects related to outdoor $PM_{2.5}$ exposure at concentrations below current national standards (Rice et al. 2016, 2018; Di et al. 2017). It is therefore important to raise awareness of indoor air quality issues among school administrators, engineers, and policymakers.

In LASSO models, a broad range of exposure determinants at the outdoor environment, school, and room level were examined, and several factors were found to contribute significantly to indoor pollutant concentration. The most important predictor associated with indoor exposure in the models was outdoor air pollution, accounting for 53.9%, 63.4%, and 34.1% of the $PM_{2.5}$, BC, and NO_2 variability, respectively. This result underpins the fact that stricter policies aiming at reducing outdoor air pollution emissions, such as the Clean Air Act standards, are still the most effective way to reduce children's exposure to air pollution in schools. Given that outdoor pollution penetrates indoors, local city-wide or neighborhood guidelines and initiatives (e.g., retrofitting buses; traffic reduction or rerouting) can further reduce outdoor air pollution exposures, hence improving indoor air quality and children's health.

Further improvement of the potentially reparable predictors of indoor school pollution that we defined in the present study may further improve health for students. School-based predictors included furnace servicing, the presence of a basement, annual income, building type, building year of construction, number of classrooms, number of students, and type of ventilation and explained 18.6%, 26.1%, and 34.2% of $PM_{2.5}$, BC, and NO_2 levels, whereas classroom-based predictors included classroom floor level, classroom proximity to the cafeteria, number of windows, frequency of classroom cleaning, and windows facing the bus area and explained 24.0%, 4.2%, and 29.3% of $PM_{2.5}$, BC, and NO_2 concentrations, respectively. These findings can provide key information regarding controllable exposure factors in managing schoolchildren's exposure and suggest that some reparable factors may contribute to the reduction of indoor school pollution exposures in the U.S. urban setting. Servicing of furnaces, the outdoor location of school bus parking, increasing the airtightness of the building envelope, and building cleaning are examples of factors that influenced indoor classroom $PM_{2.5}$, BC, and NO_2 levels and are ameliorable to change to reduce exposure for inner-city schools and schools located in poor neighborhoods.

Future targeted interventions should consider the use of mechanical ventilation, with attention to optimal air exchange rates in schools and the application of appropriate filters in the heating, ventilation, and air conditioning systems that can effectively reduce the contribution of outdoor air pollution indoors. In addition, further work should assess whether indoor classroom pollution is improved when school classrooms face parks or other green areas and when schoolyards overlook the calmest streets, instead of the busiest road around the school.

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